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On the design of Nutrient Film Technique hydroponics farm for smart agriculture

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ABSTRACT

Smart farming is seen to be the future of agriculture as it produces higher quality of crops by making farms more intelligent in sensing its controlling parameters. Analyzing massive amount of data can be done by accessing and connecting various devices with the help of Internet of Things (IoT). However, it is not enough to have an Internet support and self-updating readings from the sensors but also to have a self-sustainable agricultural production with the use of data analytics for the data to become useful. In this work, we designed and implemented a smart hydroponics system that automates the growing process of the crops using Bayesian Network model. Sensors and actuators are installed to monitor and control the parameters of the farm such as light intensity, pH, electrical conductivity, water temperature, and relative humidity. The sensor values gathered are used in the building the Bayesian Network, which classifies and predicts the optimum value in each actuator to autonomously control the hydroponics farm. Results show that the fluctuations in terms of the sensor values were minimized in the automatic control using BN as compared to the manual control. The prediction model obtained 84.53% accuracy after model validation and the yielded crops on the automatic control was 66.67% higher than the manual control.

1. Introduction

As smart machines and sensors crop up on farms and farm data grow in quantity and scope, farming processes will become increasingly data-driven and data-enabled. Rapid developments in the Internet of Things (IoT) are propelling the phenomenon of what is called smart farming.

Precision agriculture (PA), which is also known as site-specific farming, represents a data-driven agricultural management system. The PA management system is designed to improve the agricultural processes by enabling continues soil/plant monitoring and precise treatment. With the latest technology, cloud-based IoT control center collects and processes real-time data of both crops and environment with regard to planting, fertilizing, and harvesting crops, at appropriate time and duration. Through this way, IoT-embedded PA can be achieved to increase the quality, quantity, sustainability, and cost effectiveness of agricultural production (Hassan, 2018).

While PA is just taking in-field variability into account, smart farming goes beyond that by basing management tasks not only on location but also on data, enhanced by context and situation awareness, triggered by real-time events (Wolfert et al., 2017). IoT may assist in agriculture and breeding. Monitoring and controlling agricultural production and feed by using advanced sensor systems are further applications of IoT. Such systems will ensure the health of plant origin products intended both for human and animal consumption (Borgia, 2014). In addition, by installing the remote monitoring terminal on the large-scale intelligent agricultural machinery and developing the related mobile application software and server software, the agricultural machinery service management system can help those special companies to provide high efficient and low-cost production services to farmers which is based on the modern technology. The system can help promote the use of large-scale agricultural machinery and liberate a large number of rural labor force to participate in industrialization and urbanization process (Zhang et al., 2017).

Although IoT is getting momentum to enable technology for creating a ubiquitous computing environment, special considerations are required to process huge amounts of data originating from, and circulating in, such a distributed and heterogeneous environment. Collecting and analyzing the data circulating in the IoT environment is

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where the real power of IoT resides. To this end, applications utilize machine learning and data-mining techniques to extract knowledge and make smarter decisions (Khodadadi et al., 2016). To assess the future using these data streams, high-performance technologies that identify patterns in the data as they occur is needed. Once a pattern is recognized, metrics embedded into the data stream drive automatic adjustments in connected systems or initiate alerts for immediate actions and better decisions.

The goal of this work is to develop a hydroponics farm system for smart farming of vegetables production, notably leafy vegetables, with the use of sensors that are integrated for data gathering and actuators to autonomously stimulate the system. Hydroponics is one of the farming technologies that is considered as the quickest growing sector of agriculture and can govern food production in the future. Hydroponics farming fully provides the right amount and type of nutrients that the plants need at a right time and can be installed indoor to maximize available space. Soil related problems were solved by hydroponics like growing plants that needed hard-to-maintain soil conditions, minimal weeding and easier to harvest. Combining hydroponics with IoT can lead to prosperous crop harvest and potentially increase crop production.

Paper contributions: This paper makes the following contributions: (1) develop a hydroponics farm integrated with sensors that gather and monitor plant parameters from the physical environment; (2) generate a Bayesian Network model based on sensor data that classifies and predicts actuator levels to automate the system; (3) develop a web interface via a cloud platform to remotely access, monitor and control the farm; and (4) measure the reliability and improvement gain of the automated system as compared with manual system.

The rest of the paper is organized as follows. Section 2 presents the related work. In Section 3, we discuss an overview of hydroponics system. In Section 4, we discuss the actual testbed environment and deployment used. In addition, we also present our results in this section. Finally, Section 5 concludes the paper.

2. Related work

Relevant works have been published in designing and implementing smart farming. A conceptual model and system design for decision support of smart farming with network sensor applications in order to perform necessary tasks required for farmers has been proposed with a comprehensive model using IoT approach which will be applied to agriculture. Data acquisition via sensors, control and tasks management, and data analysis are considered in the development of model and system design. This system helps farmers facing problems of tasks management and planning, environment factors measurements, and information distribution (Suakanto et al., 2016). On the other hand, Agri-IoT, a semantic framework for IoT-based smart farming applications, supports reasoning over various heterogeneous sensor data streams in real-time. It can integrate multiple cross-domain data streams, providing a complete semantic processing pipeline, offering a common framework for smart farming applications. It also supports large-scale data analytics and event detection, ensuring seamless interoperability among sensors, services, processes, operations, farmers and other relevant actors, including online in-formation sources and linked open datasets and streams available on the Web (Kamilaris et al., 2016).

Another work specified a farm management system that takes advantage of the new characteristics that future Internet offers. These come in terms of generic software modules that can be used to build farming related specialized modules. Functional architecture of this farm management system and provide an operational example has been included and analyze the technological enablers that will make the architecture a reality (Kaloxylos et al., 2012). Another work builds an autonomous gardening robotic vehicle which automatically identifies and classifies the plant species using feature extraction algorithms. It measures the key parameters for gardening such as temperature, humidity, heat level, wind speed, wind direction and soil moisture. The data acquired from the on-board sensors of the gardening rover are sent to the cloud storage platform on a regular basis. Based on the acquired data and history, future predictions are made to maintain the garden more effectively and efficiently. A website and an android application are developed for monitoring and controlling the rover from a remote area. The system is a combination of new technologies involving an interdisciplinary approach to carry out precision gardening using IoT (Kumar et al., 2016).

A new structure integrated data acquisition system and intelligent control system on agricultural facilities wherein it improved the efficiency and affectivity to pro-duction and promoted an information-based and intelligent level of comprehensive agricultural zone has been proposed. The system integrates sensor nodes, wireless networks and sensor configuration system with intelligent frequency conversion irrigation function and automatic control function of greenhouse to gather data on greenhouse environment parameters and biological in-formation (Guo and Zhong, 2015). Furthermore, another work presented a connected farm based on IoT systems which targets to offer smart farming system up until to end user. As an ease for end users, they have implemented smartphone application that allows them to monitor and control the different farms connected to the system via IoT (Ryu et al., 2015).

Most of these works were designed to have a generic IoT-based framework for future smart farming applications. Only few of them were able to implement an actual testbed to verify the performance of the proposed frameworks. In addition, none of these works have considered integrating a hydroponics farm with machine learning that performs data analytics to control existing parameters governing the growth of the plants. This work intends to fill this gap in the literature.

3. Overview of IoT-based hydroponics system

The whole system is comprised of three major components: sensors, data analytics, and web interface. Hardware includes a hydroponics farm built with a sensor network for the purpose of monitoring and control ling the system. Software is composed of the data analytics and cloud server needed for data storage and predictive analysis. The web interface serves as the graphical interface of any user to remotely access the farm. The complete process of the system is shown in Fig. 1. The IoT-based hydroponics system is design to create a closed feedback loop that monitors and controls the farm based on the parameters needed by a specific variety of plant (Alipio et al., 2017).

Plants grown under hydroponics farming extract the nutrients they need from a water-based solution. How-ever, not all plants can be produced by this farming technique. Leafy plants are easier to grow and their roots are more lightweight than the other types (Genuncio et al., 2012). Iceberg type of lettuce is used since the growing time of this plant is the suitable to the duration of this work. Since the farming method eliminates the use of soil and focuses on the parameters concerning on the air and water in the surroundings, other factors such as the pH level, electrical conductivity and temperature levels are also significant in hydroponics farming. In addition, maintained light intensity ensures the efficiency rate of growing the plant. As data pass through the cloud server, time series charts are being generated and uploaded on the website.

The flow process of the whole system is shown in Fig. 2. The process starts with the initialization of connections among the sensors, microprocessors (Arduino) and microcomputer (Raspberry Pi). Next, sensors gather data from the physical hydroponics farm environment. All the data gathered by each sensor is sent to the cloud service platform (ThinkSpeak) via the Internet. This platform generates real-time series charts available via web interface for remote monitoring of users. In addition, the system's web interface provides options for the user either to manually or automatically control the actuators of the farm. If the

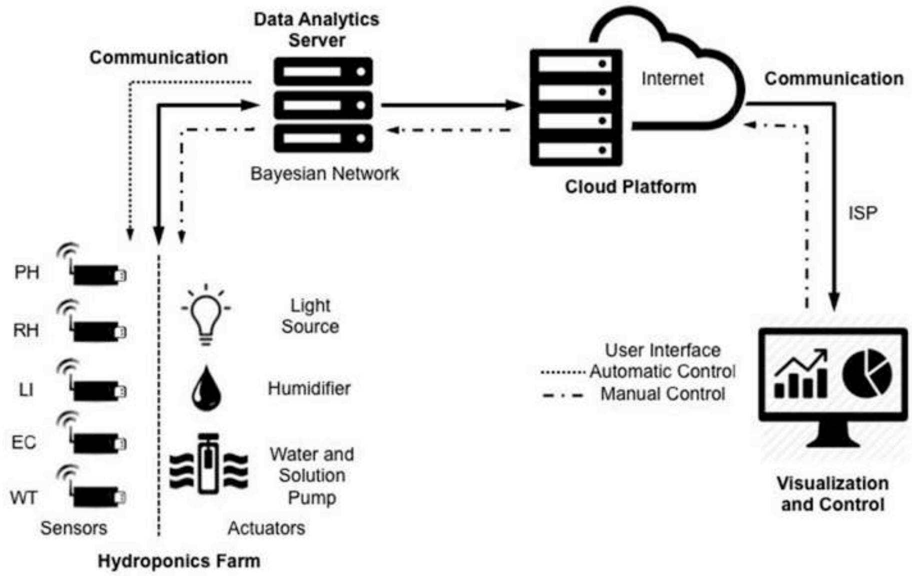


Fig. 1. System overview of smart hydroponics system.

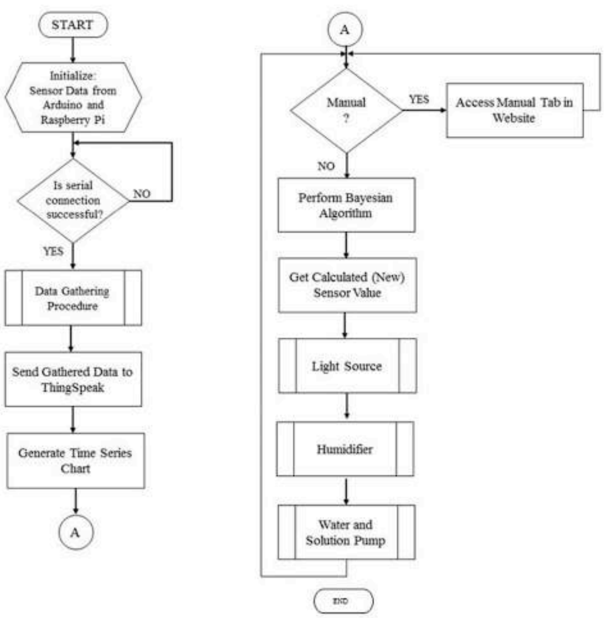


Fig. 2. System flow process.

user chooses the manual control, all actuations will be manually adjusted based on the pure knowledge of the users. On the other hand, if the user chooses automatic control, the system will use the prediction model generated using Bayesian Network algorithm to control all the actuations of the farm.

3.1. Construction of hydroponics farm

The construction of the hydroponics farm utilizes a Nutrient Film Technique (NFT) (Cooper, 1996) method with a narrow stream of water containing the dissolved nutrients needed for plant growth is repeatedly circulating past the roots of the plants through a watertight gully, also known as channels. It is composed of 16 potholes and a reservoir houses the water flowing in and out of the channels using a submersible water pump. The water flow rate based on the actual submersible pump is 260 L/hour (68.68 gallons/hour). The water flowing in each pothole contains the dissolved nutrient solution. We used a locally available

Table 1
SNAP chemical composition and concentration.

SNAP A	SNAP B
In elemental form (% weight/volume)	
Nitrogen: 6.10	Phosphorus: 0.38
Calcium: 4.25	Magnesium: 0.49
Potassium: 3.09	Iron: 0.15
Chemical properties	
pH: 2.2	
Boiling point: > 100 °C	

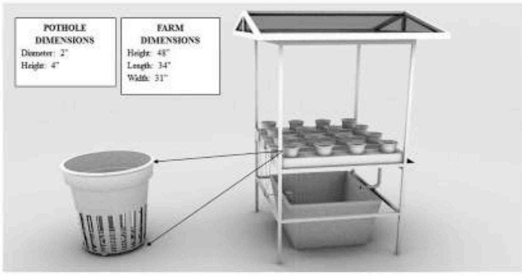
Simple Nutrient Addition Program (SNAP) (Holmer et al., 2013; Simple Nutrient Addition, 2014), which is composed of two solutions SNAP A and SNAP B. Table 1 shows the chemical composition of each SNAP solution and their corresponding percentage concentration.

A net covers the whole farm to reduce the ingress of pests and to easily control the humidity around the farm. The hydroponics farm also used an UV plastic roofing to reduce the abrupt changes brought by changing weather conditions. A 3D model design of the hydroponics farm is shown in Fig. 3.

3.2. Hardware and sensor devices

The sensor network is comprised of five different sensors that monitor different parameters needed for plant growth namely pH level (PH), electrical conductivity (EC), relative humidity (RH), light intensity (LI), and water temperature (WT) as suggested in (Genuncio et al., 2012). These sensors are connected to a microcomputer Raspberry Pi (RPI) (Raspberry Pi, 2017). RPI can handle larger amount of data and operate better in tedious processes as shown in Fig. 4 than microcontrollers. Furthermore, it is easy to install with various types of sensors, and can function as a cloud data logger, which make it an ideal micro-processor for the hydroponics system. The accuracy of each sensor is tested to guarantee that they will give correct data from the farm. For the actuation, we used light bulb to adjust light intensity, humidifier to control the humidity, and motor pumps to draw water and liquid solution into the potholes.

Fig. 5 shows how the sensors and actuators interact with the hydroponics environment. The sensors used for electrical conductivity, pH level, and water temperature are probed directly onto the reservoir. The sensors measure the current level and concentration of the solution



(a) Farm and pothole dimensions

(b) Farm with pest net cover

Fig. 3. 3D design of hydroponics farm.

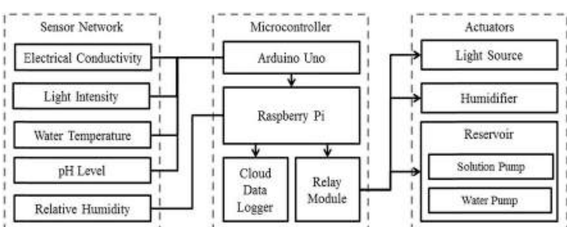


Fig. 4. Sensor and actuator components.

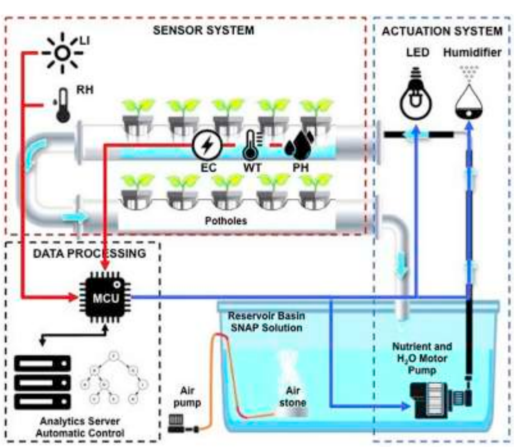


Fig. 5. Sensor actions and actuator responses.

before pumping the water into the gullies. On the other hand, the relative humidity sensor is placed on the farm together with the crops to monitor the humidity of the surrounding while light intensity sensor is mounted on top of the roofing to monitor the incoming light. Each of the sensor has recommended sensing ranges in which every range values should be met based on the threshold values suitable for plant growth. Table 2 shows the approximate threshold values of each sensor as suggested in (Genuncio et al., 2012). These sensor values serve as the hyperparameter of the prediction model using Bayesian Network.

Table 2
Approximate upper and lower threshold values and conditions for each sensor.

Sensor	Value/Condition
Relative Humidity (RH)	Min ≅ 50 Max ≅ 80
Light Intensity (LI)	100–200 μmol/m^2/s
Water Temperature (WT)	Min ≅ 22°C Max ≅ 28°C
pH Level (PH)	Min ≅ 5.5 Max ≅ 7.0
Electrical Conductivity (EC)	Min ≅ 0.9 mS/cm Max ≅ 2.1 mS/cm

3.3. Data analytics using Bayesian inference

In order to make the hydroponics farm autonomous in initiating alerts for immediate actions, we used a machine learning algorithm called Bayesian Networks (BNs) to ascertain data transmitted by each sensor. BN is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph which is based on *a priori* probability or Bayes Theorem (Zhou et al., 2016). The algorithm implements an input-based process based on the inputs (features) and generate the appropriate output decisions (labels). BNs are better suited to capture the complexity of the underlying decision-making process, taking into account the many inter-dependencies among the variables. Moreover, it provides a global view of the variables' associations compared with decision tree type of classification learning (Zhang et al., 2016; Zhang and Wang, 2015).

In our system, the algorithm learns based on the data coming from the different sensors. The greater the number of datasets analyzed, the more accurate the BN pre-diction will be. Fig. 6 shows the overview of the BN classification model used for the automatic control of the farm. The features (input data) include all the sensor values from PH level, electrical conductivity, relative humidity, light intensity, and water temperature (WT). On the other hand, the labels (predicted output data) include all the actuation for light bulb, humidifier and motor pump.

3.4. Cloud server and web interface

The data gathered by the sensors and the decisions generated by the BN model are transmitted through a cloud platform. Using a virtual database, the sensor values are uploaded to the cloud server in text format. This is to maintain smaller file size and will not require larger storage. The data from cloud is viewed in a time series chart displayed on the web-based visualization as shown in Fig. 7. This allows the user to easily track the trend of values in each sensor real-time. Before the user could access the main page, the website asks for the administrator's password to ensure privacy and confidentiality of the system. Furthermore, this also serves as a virtual logbook for all the sensor data streams. The web interface is composed of two pages namely automatic control and manual control. In manual control, the user has the authority to change the states of the relay and controls the operation of any actuator in the system. In automatic control, the decisions based from the BN pre-diction model are used to autonomously control all the actuators.

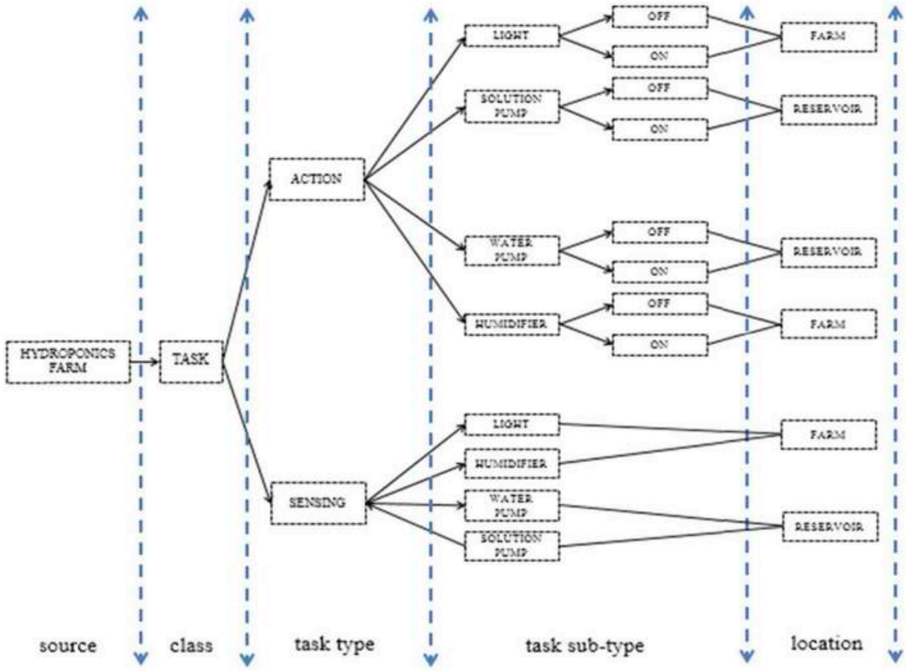


Fig. 6. Bayesian Network (BN) classification based on sensor pa-rameters

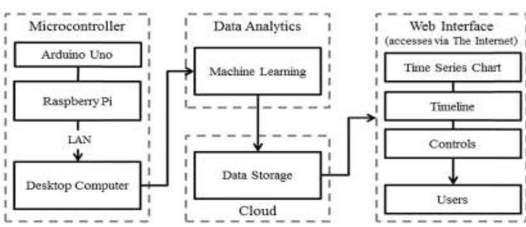


Fig. 7. Processor, cloud and web-based user interface.

3.5. Actuator subroutine

The actuators for this system are the controlling elements for efficient plant growth. Each actuator is indirectly connected to a sensor wherein if the detected value from the sensor is not within the range of reference values, the corresponding actuator is energized until the threshold values are met. These actuators are controlled either manually or automatically.

During manual control, the state of the actuators is controlled by the user, which is assumed to have a very good knowledge on hydroponics farming. The duration as to when the actuation will halt is also dependent on the user. A control panel for each actuator is displayed on a web interface. On the other hand, the automatic actuation will only commence if the user chooses the automatic control. In this case, the duration and actuation are all autonomous. The light source actuator is dependent on the parameter light intensity while relative humidity is the parameter dedicated for humidifier. In addition, both pH and electrical conductivity are used as the parameters in changing the state of the relays of the water solution and SNAP solution solenoids. Since the system is adaptive and autonomous, it does not require the user to have a very good background on hydroponics farming and solely depends on the BN prediction outputs for actuation.

4. Testbed deployment, results and discussions

4.1. Hydroponics farm setup

The hydroponics farm is deployed at a local farm residence. The actual farm has a dimension of 2.2 m × 2.74 m x 2.35 m. The area is open and well-lit, free from isolation and any obstruction that might interfere with the growing plants. Fig. 8 shows the actual testbed setup of the system.

Fig. 8. Actual testbed setup.

4.2. Generation of prediction model using BN

The generation of BN model utilizes data continuously gathered for 27 days (24 h per day) which resulted to a total of 6,881 datasets (outliers omitted). From this available dataset, 5,505 instances are used as training set and the remaining 1,377 instances are used as testing dataset. Using Weka 3 (Weka 3, 2016) analytics tool, we generated the network classification model based on the 5,505 training dataset and obtained 84.53% accuracy after model validation. The rest of the evaluation results of the training dataset obtained from Weka Explorer are shown in Table 3.

Kappa statistic is a measure of how closely the instances classified by the machine learning classifier matched the data labeled as ground truth. The model achieved a moderate classification based on Lan-dis

Table 3
Summary of evaluation on training model.

Criteria	Value
Kappa Statistics	0.6095
Mean Absolute Error	0.2153
Root Mean Squared Error	0.3195
F-Measure	0.8440
Accuracy	0.8450

and Koch and fair-to-good classification based on Fleiss (U. D. of Health, 2013). In addition, the model also achieved a high F-score measurement (best case = 1, worst case = 0), which indicates a very good test accuracy in terms of precision and recall.

Due to page limitation, the network shown in Fig. 9 only shows a part extracted from the whole BN model generated from the data of each sensor. This BN prediction model graphically represents the joint probability distribution of a set of random variables from different sensor data. It is a directed acyclic graph that shows different set of conditional probabilities such that it computes the posterior probability distribution for a set of query variables (setting of actuators), given values for some evidence variables (sensor data). At a certain sensor parameter, the large amount of data from the other four sensor parameters are fed to the network wherein the data are analyzed and predictions are per-formed. The output of each network is dependent on the other four controlling sensor parameters being fed to their corresponding model. This is to establish a probabilistic relationship between sensor values as each value are predicted. Biasing and the occurrence of human error are minimized as the decisions from BN control each actuator. In this way, the accuracy is improved and the sensor thresholds are achieved real-time. Simplified BN from each sensor are shown in Fig. 10.

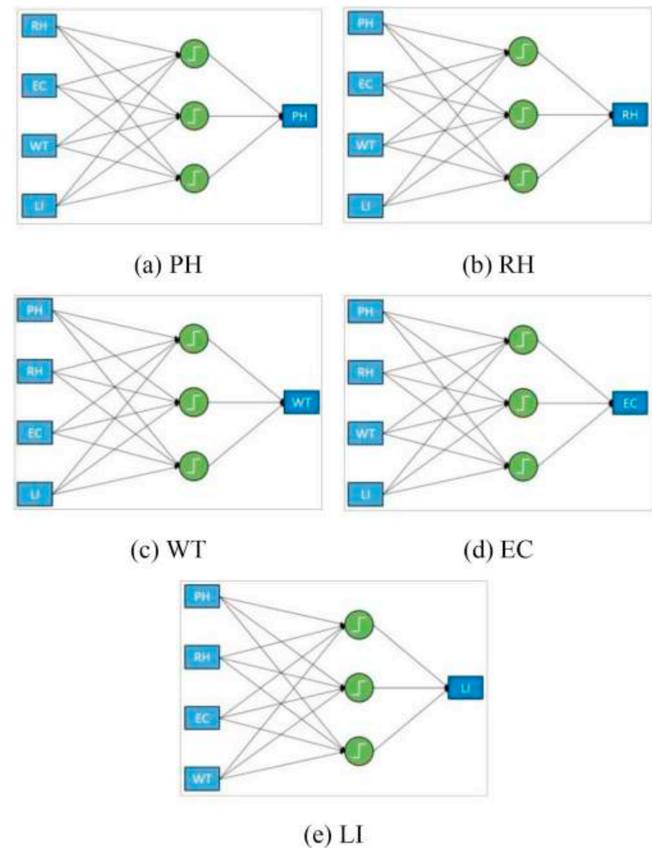


Fig. 10. Simplified Bayesian Network for each sensor.

4.3. Sensor data and actuation response accuracy

After installing the sensors onto the hydroponics farm, their accuracies are tested by measuring the level of precision at which they detect the correct values. Since the system is also installed with actuators, the ac-curacy is tested and their responses are monitored upon actuation. The sensors are considered the critical portion of the hardware component since the BN model depends on the data coming from these devices. Each sensor is fed with a test unit with known parameters. For each accuracy test, 30 trials are obtained. The data are analyzed by calculating its central tendencies, particularly the mean, median, and mode. Moreover, the standard deviation is calculated to show how much each data is distanced from each other. The interval per data gathering is 30 s and averaged on a 15-min interval. Table 4

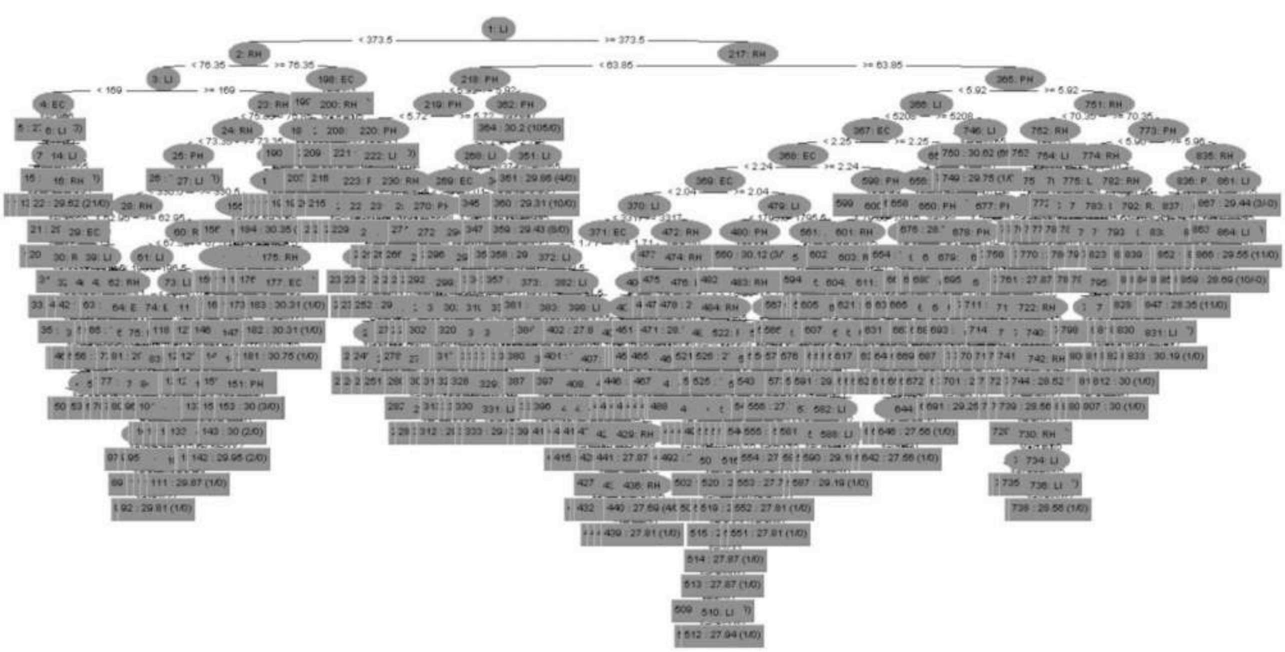


Fig. 9. Generated Bayesian Network from sensor data (extracted).

Table 4
Accuracy test response of each sensor data.

	PH	RH (%)	EC (mS/cm)	WT (Celsius)	LI (lx)
Mean	7.00	74.33	2.20	27. 95	96.83
Median	7.01	74.45	2.48	27.87	97.00
Mode	7.02	74.70	2.48	27.87	97.00
Std. Dev.	0.0163	0.4836	0.4626	0.4024	0.5307

shows the results of measure of the central tendencies.

The values of the median and mode for all sensors are approximately equal. This suggests that the middle value given a set of data is also equal to the most frequent value. On the other hand, the average value of each sensor does not deviate farther. These data are used in the generation of the normal distribution curve, which illustrates the closeness of each measure. This means that the mean, median, and mode for each sensor does not deviate from each other. This deviation can be attributed to the delay that the data has incurred during transmission. Due to the small difference between the different measures, the data delivered to the website is reliable. This also implies that the values transmitted by each sensor are accurate even after being subjected to longer duration of testing.

4.4. Dashboard user interface

The dashboard interface uses an IoT cloud platform called ThingSpeak (ThinkSpeak, 2017) as shown in Fig. 11 wherein the trends of the data from the sensors are monitored by the user. The graphs are designed for the purpose of easy accessing and monitoring for the targeted users, which are the farmers, who only requires to view the desired values of each parameter. In addition, the design is kept simple and user-friendly. There are two websites made mainly for viewing and controlling purposes. The first website is deployed using Firebase (Firebase, 2016). This features viewing and monitoring of real-time sensors data stream in time series charts via the Thingspeak plat-form. The second website is deployed to My NoIP (My NoIP, 2017) directly to microprocessor. This features both monitoring and controlling of the actuators.

Figs. 12 and 13 show the dashboard user interfaces for manual and automatic controls, respectively. For manual control interface, four actuators (water pump, solution pump, humidifier and light source) are access and controlled via the Internet based from the decision and judgment of the user. In addition, the amount of time in doing the actuations is indefinite for this inter-face. On the other hand, in the automatic control inter-face wherein the states of the actuators are controlled based on the predicted values of BN, the duration of the actuation is definite since it has a feedback mechanism wherein it continuously monitors and compares the predicted and current values of each parameter. As long as both of these values are not equal, the actuation continues based from the output of the BN prediction model.

Fig. 12. Manual control dashboard interface.

Fig. 13. Automatic control dashboard interface.

4.5. Manual control vs automatic control

We also compared the performance of the proposed automated system with a manual-based configuration. For the manual system, the one who has the access on the farm should be knowledgeable on the values of each actuator must maintain. In this study, we assumed that a well-experienced hydroponics farmer controls the manual system. Should the value deviate, the user (farmer) can control all the actuations through the web inter-face as shown in Fig. 12 until they reached the desired value. Therefore, proper precautions should be observed when utilizing the manual control.

The comparison of each sensor response between the automatic control using BN and manual control are shown in Fig. 14. In manual control, higher fluctuations on the sensor values are obtained. This is due the minimal supervision on the system since the actuation only relies on the judgment of the user. On the other hand, the trend of values for automatic control using BN is relatively constant. Lesser

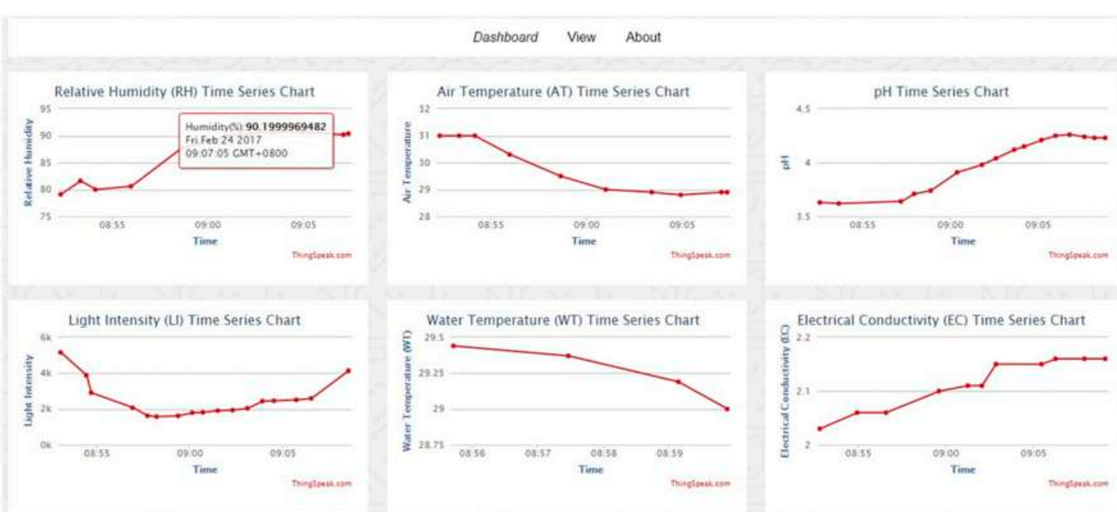


Fig. 11. Time series chart monitoring dashboard for user interface.

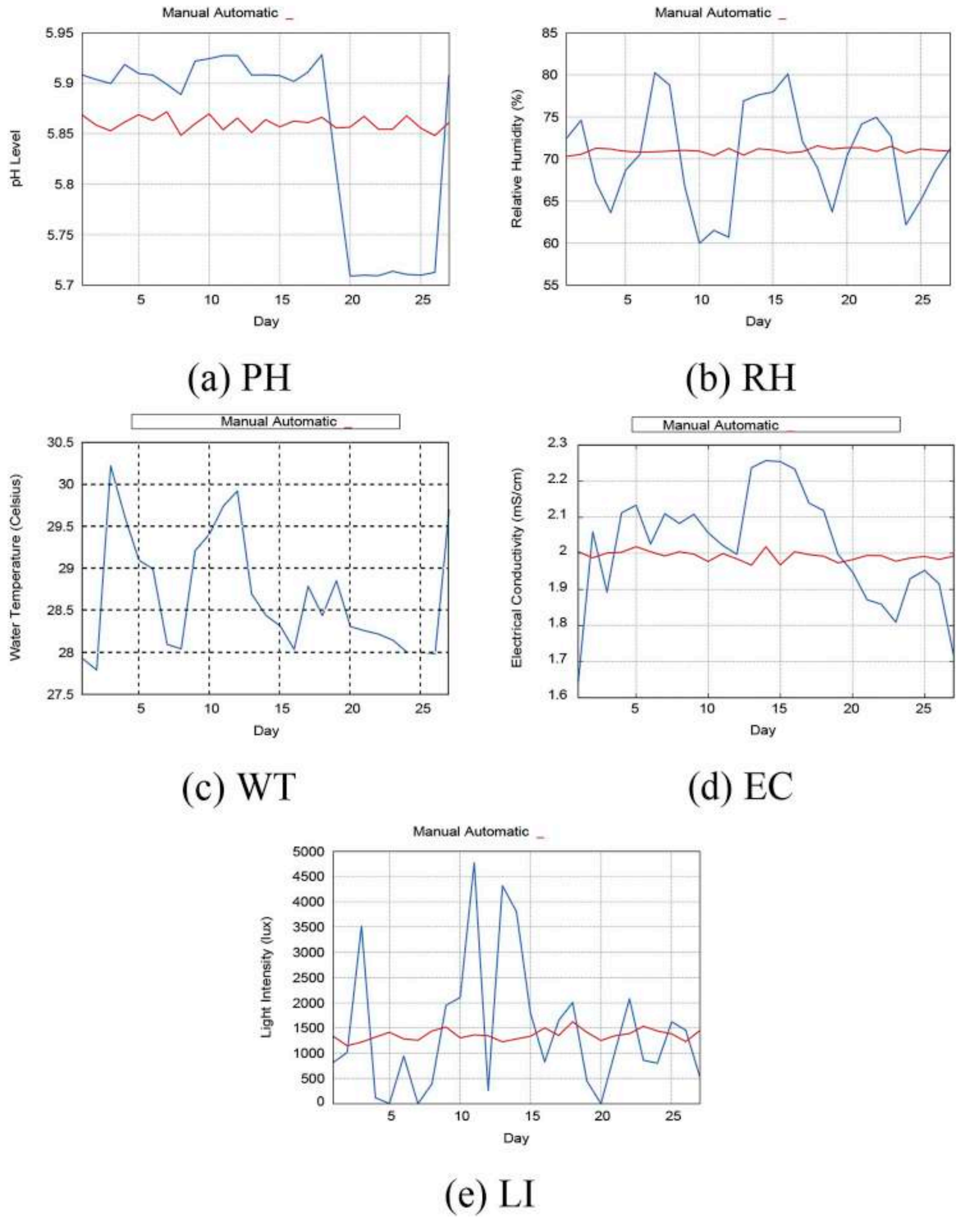


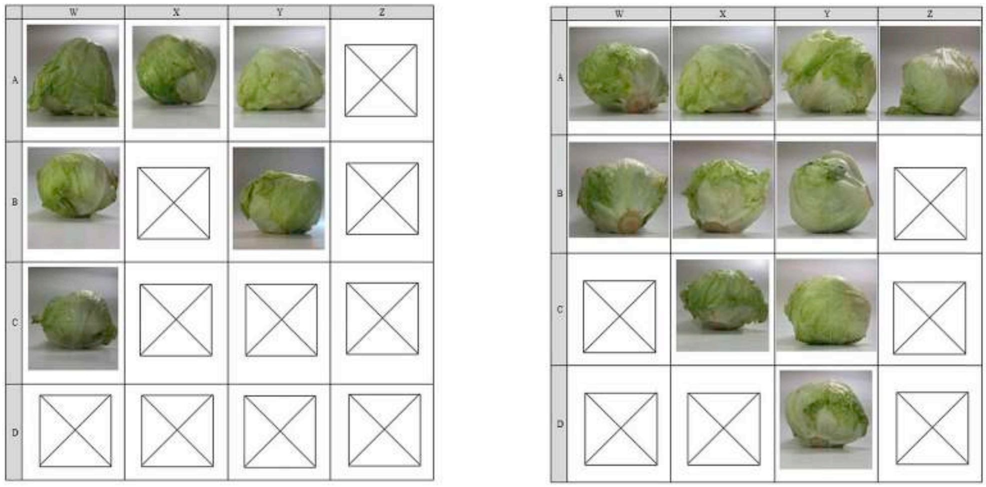
Fig. 14. Comparison of sensor data response between manual and automatic controls.

deviations are obtained since the BN output decisions automatically adjust the values and control the system. Due to the intricate supervision established using BN algorithm, values for each sensor are maintained over the course of the data gathering. Moreover, this suggested that the implementation of the BN model is effective in establishing an adaptive and controlled environment for hydroponics farming.

Fig. 15 shows the actual iceberg lettuces produced from manual and automatic controls, respectively. A total of 16 iceberg lettuce seedlings were grown using the hydroponics farm system and monitored for almost a month. Row positions are represented by A, B, C and D while W, X, Y and Z represent the column positions.

The boxes which contain X marks indicate that the lettuce crops in this pothole did not successfully grew with respect to standard parameters used by horticulturist and local farmers. The first row of the farm is represented by combination of letters AW, AX, AY and AZ while the combination DW, DX, DY and DZ represented the last row of the farm. Initially, the water and nutrient solution come from the container below the hydroponics farm. The majority of the nutrients that are absorbed by the crops from the first row contribute to the withered crops from the last row. The presence of pests and other environmental factors such as air pollution also contributed to the withered crops of the farm.

During the manual control, the system produces only 6 out of 16 iceberg lettuces. The dependency of actuators to user is a major factor to this low yield. For automatic control using BN, the system produces 10 out of 16 iceberg lettuces. The relatively high yield, as compared to the manual control, is due to the automatic-controlled system and the implementation of BN predictive analysis, which was proven to be effective due to the intricate monitoring and controlling of the system. In addition, other external factors in which the hydroponics system cannot control such as weather and insects could also be factors. Table 5 shows the summary of comparison of the crops yielded between the manual and automatic controls. The decline of gain difference is attributed to the shape of the crop. Since the circumference is measured horizontally, the increase on the circumference is smaller. However, the gain is distributed fairly among other parameters such as the height and weight. In the automatic system, a large amount of data is gathered and



(a) Manual control (b) Automatic control

Fig. 15. Matrix position of lettuce grown in potholes.

Table 5
Comparison of yielded crops.

Parameters	Manual	Automatic	Difference
Weight (g)	0.35	0.44	27.25%
Height (cm)	10.58	12.75	20.47%
Circumference (cm)	35.27	38.52	9.22%
No. of Leaves	10	14	40.00%
No. of Yielded Crops	6	10	66.67%

make useful through data analytics. The BN prediction model provides the optimum values required for each governing parameter. This results to a more intricate control over the different parameters which contributes to a higher quality of yielded crops compared with manual control. Since the farmers are eyeing for more sustainable crop production, this integration offers higher crops survival rate at reasonable cost.

Tables 6 and 7 show the central tendency values of sensor data obtained from the manual and automatic controls, respectively. It can be observed that the automatic control achieved lower standard deviation values compared with the manual control. Lower standard deviation implies that outliers are reduced, if not, minimized. Also, this suggests that the data obtained in the automatic control are controlled effectively. As soon as the current value is not equal to the calculated value from the BN model, the actuator is immediately energized, thus adapting the value of the parameter being controlled.

The maximum round-trip time that is acceptable in measuring and analyzing the packets is 95 ms (Gandhi et al., 2014) for this type of network application. Fig. 16 shows the graph of the round-trip time of accessing the cloud via the web-based user inter-face located 10 km away from the hydroponics system.

Table 6
Central tendencies of sensor data from manual control.

	PH	RH (%)	EC (mS/cm)	WT (Celsius)	LI (lx)
Mean	5.86	70.97	1.99	28.73	1370.19
Median	5.90	72.10	1.99	28.37	943.00
Mode	5.91	79.30	2.26	28.00	1.00
Std. Dev.	0.09989	7.09189	0.22615	0.85170	1792.288

Table 7
Central tendencies of sensor data from automatic control.

	PH	RH (%)	EC (mS/cm)	WT (Celsius)	LI (lx)
Mean	5.86	70.97	1.99	28.73	1371.02
Median	5.90	71.70	1.98	28.33	955.00
Mode	5.71	79.30	2.24	28.23	1.00
Std. Dev.	0.09974	7.07298	0.22574	0.85014	1786.180

4.6. Data delivery and accessing

For a certain period of time, the delay of data trans-mission to the website is measured. A packet sniffer tool called Wireshark (Wireshark, 2018) is used to capture all packets on the network and measure the network parameter, specifically the packet delay.

The device used to measure the round-trip time is connected IEEE 802.11 (WiFi) connection. The highest average round-trip time of packets is approximately 38 ms which is still acceptable. It assumed that this delay is dependent on some factors such as network provider, location, and time delay from the data processing of server.

5. Conclusion and future directives

This work designed and implemented an IoT-based NFT hydroponics farm using predictive analysis from Bayesian Network for smart farming. The sensor net-work composed of pH, light intensity, electrical conductivity, water temperature and relative humidity sensors are used to gather physical parameters from the farm. The data received from the sensors are process using low-cost microprocessor and are sent to an IoT cloud platform. Actuators such as water pump, solution pump, humidifier and light source are triggered in order to adjust the system's parameters. Smart farming was integrated with Internet of Things (IoT) by analyzing the large amount of data sent from the sensors. These datasets gathered for almost one month are used to generate BN, which then performs prediction of output decisions to autonomously control the system. Since the Internet plays a significant role on IoT-based applications, delay would always be present during data trans-mission. In addition, a web interface is developed for the user to access the farm

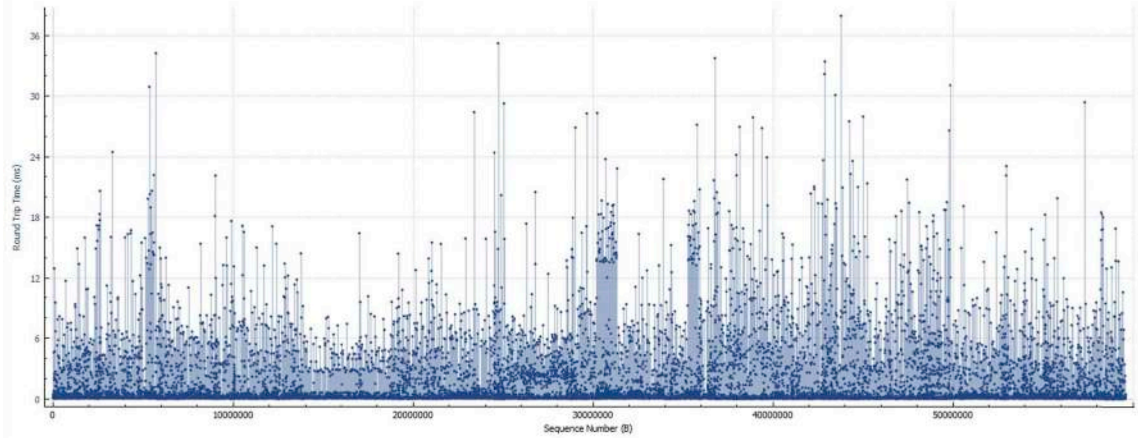


Fig. 16. Total round-trip delay accessing of web-based user interface.

remotely. Two websites are deployed via My NO-IP and Firebase for viewing, monitoring and controlling the actuators of the farm. For the results, the crops yielded from using the automatic control is better than the crops yielded from manual control by 20%–60% for all parameters used for evaluating good quality crops. Due to realized real-time data automatic acquisition and data analytics of hydroponics farm parameters and biological information, the user/farmers can achieve good economic and ecological benefits, and the great significance to the development of modern agricultural information-based intelligence.

In the future, we consider the use of cameras as it will allow easier monitoring of the quality of crops by real-time video streaming via the Internet. Moreover, learning can be implemented by combining deep learning to BN through image processing from camera images to analyze other plant parameters such as the shape and color and improve the accuracy of prediction. To further increase the accuracy of prediction model, the data gathering procedure must be longer to generate larger datasets. In addition, since the workload of the microcomputer increased due to two different farm controls, it is recommended to use higher microprocessors systems to support higher processing power and clock speed and enables wireless connection between the farm and the Internet. In terms of user interface, a personalize mobile application can be designed specifically fit for local farmers for remote monitoring. Furthermore, other types of crops that can grow on NFT hydroponics farm can also be used and evaluated. Different configurations of hydroponics farm such as drip system and Dutch bucket can be taken into consideration in order to increase the variety of crops that can be planted on the farm.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eaef.2019.02.008.

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